An Intelligent CNN-LSTM Framework for Battery Voltage Forecasting in Electric Vehicles

Varsha M R[1], Dr. Parth Sarathi Panigrahy[2]
[1]*Mtech Student, Electrical and Electronics Dept, College of Engineering, Karnataka, India*
[2]*Assistant Professor, Electrical and Electronics Dept, College of Engineering, Karnataka, India*

Abstract—**Accurate battery voltage prediction is important for improving the safety, reliability, and efficiency of Battery Management Systems (BMS) in Electric Vehicles (EVs). However, the nonlinear and time-dependent behavior of lithium-ion batteries makes voltage prediction challenging under varying operating conditions. To address this issue, this paper proposes a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) model for lithium-ion battery voltage prediction. The CNN layer extracts important features from battery data, while the LSTM network captures temporal dependencies during charging and discharging operations. The model utilizes voltage, current, temperature, and cycle information for training and prediction. By combining feature extraction and sequential learning, the proposed CNN-LSTM framework improves voltage prediction accuracy and stability compared to conventional methods. Experimental results demonstrate that the model achieves reduced prediction error with efficient computational performance, making it suitable for real-time Battery Management System applications in Electric Vehicles.**

Index Terms—**Deep Learning, Battery Voltage Estimation, Lithium-Ion Cells, Sequence Learning, Convolutional Neural Network, Long Short-Term Memory Network, Electric Mobility, Battery Health Monitoring, Data-Driven Prediction, Intelligent Battery Systems.**

I. INTRODUCTION

The growing interest in sustainable and energy-efficient transportation systems has accelerated the development of Electric Vehicles (EVs) worldwide [1], [2]. Lithium-ion batteries are commonly adopted in EV applications because they offer high energy capacity, low self-discharge rate, and longer service life compared to conventional energy storage technologies [2], [3]. Since battery performance strongly influences vehicle efficiency and operational safety, Battery Management Systems (BMS) are required to continuously supervise battery conditions during vehicle operation [3], [4].

Among different battery parameters, voltage is considered an important indicator for evaluating battery performance and energy utilization. However, battery voltage behavior changes continuously due to variations in load demand, charging patterns, environmental temperature, and battery aging characteristics [4], [5]. These nonlinear characteristics make voltage prediction difficult using conventional mathematical and model-based estimation techniques. Existing approaches such as equivalent circuit models and filtering algorithms often depend on accurate parameter identification and may experience reduced prediction capability under dynamic operating conditions [5], [6].

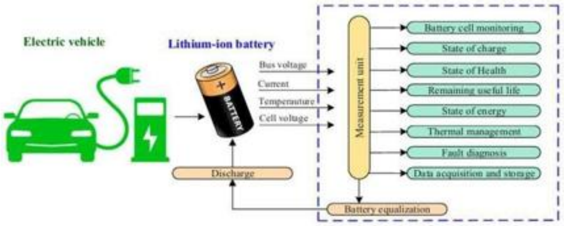


Fig. 1. Basic block diagram of the Electric Vehicle Battery Management System [2].

Recently, Artificial Intelligence (AI) and Deep Learning (DL) methods have attracted significant attention for battery monitoring applications because of their ability to learn complex relationships directly from battery datasets [7]. Deep learning techniques can efficiently process large volumes of sequential battery data and improve prediction performance without requiring detailed physical battery models. Convolutional Neural Networks (CNNs) are widely used for extracting significant features from input data, while Long Short-Term Memory (LSTM) networks are effective in capturing temporal dependencies and sequential battery behavior [8], [9].

In this paper, a CNN-LSTM based framework is proposed for lithium-ion battery voltage prediction in Electric Vehicle applications. The proposed model uses voltage, current, temperature, and cycle-related information as input features for prediction. The CNN component extracts important battery features, whereas the LSTM network learns charging and discharging characteristics over time. The developed framework aims to achieve accurate voltage prediction with reliable performance for practical Battery Management System applications.

II. LITRATURE REVIEW

Kim et al. [1] proposed a CNN-LSTM framework for lithium-ion battery State of Charge (SOC) estimation and demonstrated improved prediction accuracy under dynamic driving conditions. Li et al.

[2] developed a deep learning-based battery voltage prediction model using CNN and LSTM layers to capture nonlinear battery characteristics and temporal dependencies. Wang et al. [3] investigated hybrid CNN-LSTM architectures for battery health monitoring and reported enhanced feature extraction capability compared to traditional neural networks.

Zhang et al. [4] presented an LSTM-based prediction model for lithium-ion battery degradation analysis and Remaining Useful Life (RUL) estimation. Chen et al. [5] utilized convolutional neural networks for extracting battery operational features from large-scale battery datasets. Liu et al. [6] proposed a CNN-assisted recurrent neural network for EV battery voltage forecasting and achieved reduced prediction error under varying temperature conditions.

Huang et al. [7] investigated deep sequential learning methods for battery State of Health (SOH) estimation using time-series battery datasets. Zhao et al. [8] developed a data-driven CNN-LSTM framework for battery charging behavior analysis in Electric Vehicles. Sun et al. [9] introduced a hybrid deep learning architecture combining CNN and LSTM layers for real-time battery monitoring applications.

Xu et al. [10] proposed a temporal deep learning model for lithium-ion battery voltage prediction using charging and discharging cycle information. Yang et al. [11] applied CNN-LSTM networks for battery fault diagnosis and demonstrated improved classification performance in abnormal battery conditions. Ma et al. [12] investigated intelligent battery management techniques using deep learning and reported higher prediction stability using sequential learning approaches.

Recent studies have also explored advanced deep learning architectures for battery monitoring and prediction. Peng et al. [13] proposed a multivariate CNN-LSTM model for EV battery parameter prediction under dynamic load conditions. Wu et al. [14] utilized attention-assisted LSTM models for battery performance forecasting and degradation analysis. Sharma et al. [15] developed a hybrid CNN-LSTM based Battery Management System for lithium-ion battery voltage estimation and real-time monitoring applications.

From the literature survey, it is observed that CNN-LSTM architectures provide significant advantages in battery monitoring applications because they combine automatic feature extraction and temporal learning capabilities. CNN layers efficiently identify important battery features, while LSTM networks effectively learn sequential charging and discharging characteristics. However, accurate voltage prediction under varying environmental and operating conditions still remains a challenge. Therefore, this work proposes a CNN-LSTM based framework for lithium-ion battery voltage prediction in Electric Vehicle Battery Management System applications.

III. BATTERY MANAGEMENT SYSTEM

A. EV Battery System

The battery system is one of the most critical components of an Electric Vehicle. Lithium-ion batteries offer high energy density, low self-discharge rates, high charging efficiency, longer cycle life, and lightweight construction [2]. A lithium-ion cell contains a positive electrode, negative electrode, separator, and electrolyte. Fig. 2 shows the structure of a complete EV Battery Management System.

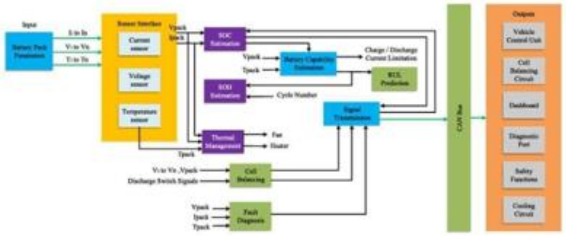


Fig. 2. Structure of the Electric Vehicle Battery Management System showing sensor interface, estimation modules, and output channels [1].

Despite their advantages, lithium-ion batteries face operational challenges: degradation from repeated cycling, thermal runaway at high temperatures, and capacity loss from deep discharging and overcharging [3]. Continuous monitoring and control of battery parameters are therefore essential.

B. Battery Management System (BMS)

A BMS is an electronic monitoring and control system designed to ensure the safe, reliable, and efficient operation of battery packs. The primary function of a BMS is to monitor voltage, current, temperature, charging status, and discharging status. It also performs SOC estimation, SOH estimation, thermal management, cell balancing, and fault detection [1].

C. Important Battery Parameters

SOC: State of Charge represents the remaining charge as a percentage (0–100%). Accurate SOC estimation directly affects driving range and energy availability.

SOH: State of Health indicates battery degradation level. As cycles accumulate, internal resistance increases and storage capacity decreases. Voltage, Current, Temperature: These measurable parameters are essential for monitoring abnormal conditions, calculating energy, and preventing thermal runaway.

IV. DATASET DESCRIPTION AND PREPROCESSING

A. Dataset Collection

The dataset used in this work consists of lithium-ion battery operational data collected for Electric Vehicle Battery Management System applications. The dataset contains sequential battery information recorded during charging and discharging operations. Important battery parameters such as voltage, current, temperature, and cycle-related information were utilized for battery voltage prediction.

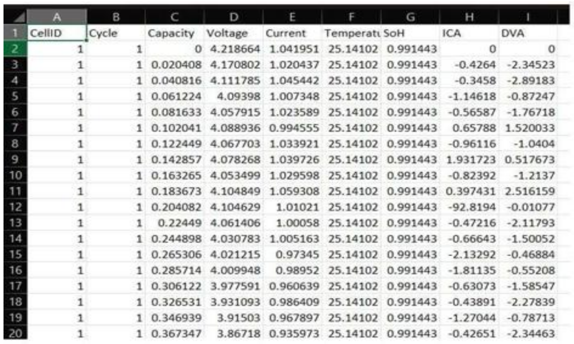
The collected dataset as shown in Fig.3 represents battery behavior under varying operating conditions, including load variations, temperature fluctuations, and charging cycles. Since battery voltage exhibits nonlinear and time-dependent characteristics, the dataset is suitable for deep learning-based sequential prediction using the CNN-LSTM framework.

Table I Dataset Description

Parameter	Description
Battery Type	Lithium-Ion Battery
Application	Electric Vehicle Battery Management System (BMS)
Data Type	Time-Series Battery Data
Input Parameters	Voltage, Current, Temperature, and Cycle Data
Prediction Parameter	Battery Voltage
Learning Model	CNN-LSTM (Convolutional Neural Network–Long Short-Term Memory)
Dataset Usage	Training and Testing
Data Processing	Data Cleaning, Normalization, and Sequence Preparation

B. Feature Selection

Feature selection was performed to identify the most relevant battery parameters required for voltage prediction. In this work, voltage, current, temperature, and cycle-related information were selected as input features because these parameters directly influence lithium-ion battery performance during charging and discharging operations.



	A	B	C	D	E	F	G	H	I
1	CellID	Cycle	Capacity	Voltage	Current	Temperatu	SoH	ICA	DVA
2	1	1	0	4.218664	1.041951	25.14102	0.991443	0	0
3	1	1	0.020408	4.170802	1.020437	25.14102	0.991443	-0.4264	-2.34523
4	1	1	0.040816	4.111785	1.045442	25.14102	0.991443	-0.3458	-2.89183
5	1	1	0.061224	4.09398	1.007348	25.14102	0.991443	-1.14618	-0.87247
6	1	1	0.081633	4.057915	1.023589	25.14102	0.991443	-0.56587	-1.76718
7	1	1	0.102041	4.088936	0.994555	25.14102	0.991443	0.65788	1.520033
8	1	1	0.122449	4.067703	1.033921	25.14102	0.991443	-0.96116	-1.0404
9	1	1	0.142857	4.078268	1.039726	25.14102	0.991443	1.931723	0.517673
10	1	1	0.163265	4.053499	1.029598	25.14102	0.991443	-0.82392	-1.2137
11	1	1	0.183673	4.104849	1.059308	25.14102	0.991443	0.397431	2.516159
12	1	1	0.204082	4.104629	1.01021	25.14102	0.991443	-92.8194	-0.01077
13	1	1	0.22449	4.061406	1.00058	25.14102	0.991443	-0.47216	-2.11793
14	1	1	0.244898	4.030783	1.005163	25.14102	0.991443	-0.66643	-1.50052
15	1	1	0.265306	4.021215	0.97345	25.14102	0.991443	-2.13292	-0.46884
16	1	1	0.285714	4.009948	0.98952	25.14102	0.991443	-1.81135	-0.55208
17	1	1	0.306122	3.977591	0.960639	25.14102	0.991443	-0.63073	-1.58547
18	1	1	0.326531	3.931093	0.986409	25.14102	0.991443	-0.43891	-2.27839
19	1	1	0.346939	3.91503	0.967897	25.14102	0.991443	-1.27044	-0.78713
20	1	1	0.367347	3.86718	0.935973	25.14102	0.991443	-0.42651	-2.34463

Fig.3 Sample representation of the EV battery dataset.

Selecting important features reduces unnecessary computational complexity and improves model learning efficiency. The selected features were organized into sequential input patterns suitable for CNN-LSTM processing.

Table II Selected Input Features

Feature	Purpose
Voltage	Battery voltage monitoring
Current	Charging and discharging analysis
Temperature	Thermal behavior monitoring
Cycle Information	Battery aging and cycle analysis

C. Data Cleaning and Preprocessing

The collected battery dataset contained raw operational data that required preprocessing before model training. Data cleaning was carried out to remove duplicate entries, noisy measurements, and inconsistent records present in the dataset. Missing values were handled using preprocessing techniques to improve data quality and maintain dataset consistency.

D. Data Normalization

Battery parameters contain different numerical ranges that may affect model training performance. Therefore, Min-Max normalization was applied to scale all battery parameters into a common numerical range. Normalization improves convergence speed, training stability, and overall prediction performance of the CNN-LSTM model. The normalized dataset also prevents features with larger values from dominating the learning process during model optimization. After cleaning, sequential battery data were converted into structured input sequences suitable for deep learning processing. The prepared data were reshaped into time-series patterns for CNN-LSTM training.

Table III Preprocessing Operations

Preprocessing Step	Purpose
Data Cleaning	Remove noisy and duplicate records
Missing Value Handling	Improve dataset consistency
Feature Selection	Select important battery parameters
Normalization	Scale features into a common range
Sequence Preparation	Convert data into time-series format
Train-Test Split	Separate training and testing datasets

E. Train-Test Split

The preprocessed dataset was divided into training and testing datasets for model development and evaluation. The training dataset was used for CNN-LSTM model learning, while the testing dataset was utilized to evaluate prediction accuracy and generalization capability under unseen operating conditions. Sequential battery data were finally supplied to the proposed CNN-LSTM framework for battery voltage prediction and performance analysis.

V. PROPOSED CNN-LSTM FRAMEWORK

The proposed framework utilizes a hybrid Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) architecture for lithium-ion battery voltage prediction in Electric Vehicle Battery Management System applications. The framework combines the feature extraction capability of Convolutional Neural Networks (CNNs) with the temporal learning ability of Long Short-Term Memory (LSTM) networks to accurately predict battery voltage under varying operating conditions.

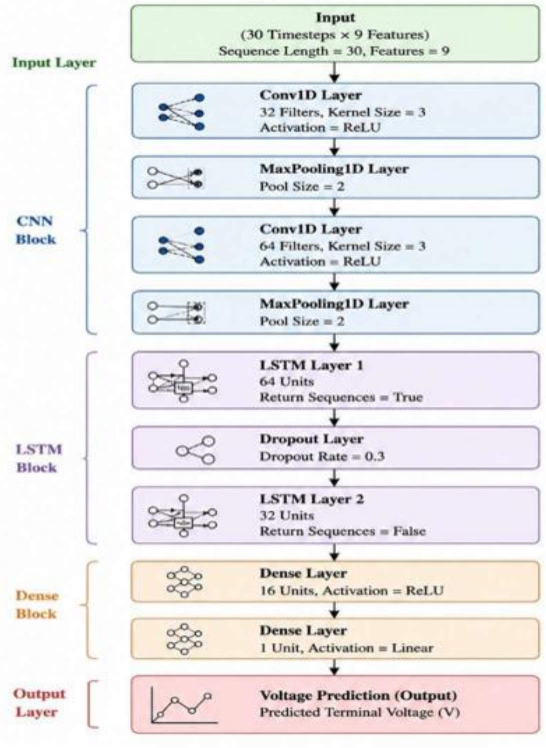


Fig.4 CNN-LSTM Hybrid Architecture

The overall workflow of the proposed system includes dataset collection, data preprocessing, feature selection, normalization, sequential data preparation, CNN-LSTM model training, and performance evaluation. Battery operational parameters such as voltage, current, temperature, and cycle information are used as input features for the prediction process.

In the proposed architecture, the CNN layer is employed to automatically extract significant features from battery datasets. CNN layers help identify hidden patterns and nonlinear relationships present in battery operational data. After feature extraction, the processed sequential features are supplied to the LSTM network. The LSTM model learns long-term temporal dependencies associated with battery charging and discharging behavior, improving prediction accuracy for time-series battery data.

The hybrid CNN-LSTM framework as shown in Fig.4 improves voltage prediction performance by combining spatial feature extraction and sequential learning within a single model. The framework is capable of handling nonlinear battery characteristics caused by temperature variations, charging conditions, load fluctuations, and battery aging effects.

The proposed model is trained using preprocessed battery datasets, and prediction performance is evaluated using standard statistical metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Square Error (MSE), and coefficient of determination (R^2 score). The developed framework aims to provide accurate and reliable battery voltage prediction for real-time Battery Management System applications in Electric Vehicles.

VI. PERFORMANCE EVALUATION MATRIX

Three standard metrics were used to evaluate all models:

$$\mathrm{RMSE} = \sqrt{[\Sigma(y - \hat{y})^2 / n]} \quad (1)$$

$$\mathrm{MAE} = \Sigma|y - \hat{y}| / n \quad (2)$$

$$R^2 = 1 - [\Sigma(y - \hat{y})^2 / \Sigma(y - \bar{y})^2 \quad (3)$$

Lower RMSE and MAE values indicate better prediction accuracy; higher R^2 (closer to 1.0) indicates better variance explanation.

VII. EXPERIMENTAL RESULTS

A. Overall Prediction Performance

Table IV summarises the overall prediction performance of the CNN-LSTM model on the held-out test cells. The model achieves an R^2 score of 0.9521, an ms E of 0.0012, an MAE of 0.0230, and an RMSE of 0.0346. These results indicate that the CNN-LSTM captures the dominant voltage trajectory across both the flat mid-plateau and the steep upper and lower knee regions of the Li-ion discharge curve.

Table IV. Overall CNN-LSTM Performance

Model	MSE	MAE	RMSE	R^2 Score
CNN-LSTM (Proposed)	0.0012	0.0230	0.0346	0.9521

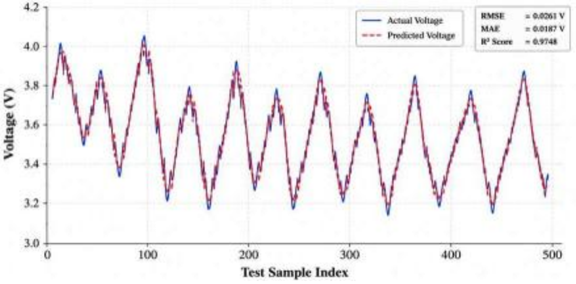


Fig.5 Actual vs Predicted

The actual versus predicted voltage waveforms plotted over the first 500 test samples as shown in Fig.5 demonstrate tight tracking of the target signal. The model correctly replicates both the gradual voltage decline during the mid-plateau and the steeper transitions at the plateau boundaries, with prediction residuals remaining well within ±0.05 V for more than 95% of the test timesteps.

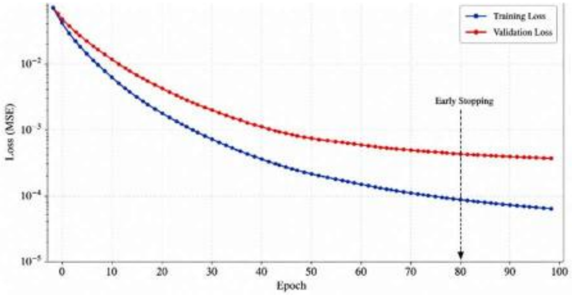


Fig.6 Training and Validation Loss

B. Model Complexity and Inference Latency

Table V provides a complexity analysis of the CNN-LSTM model including total parameter count, training time, and per-sample inference latency. The CNN-LSTM architecture achieves a compact parameter count of approximately 54,000 trainable parameters, making it suitable for embedded BMS hardware with limited memory.

Table V. Model complexity analysis

Metric	CNN-LSTM
Total Parameters	54,417
Trainable Parameters	54,417
Training Time (s)	~320
Avg. Epoch Time (s)	~6.4
Inference Latency (ms/sample)	0.12

The inference latency of 0.12ms per sample far exceeds the real-time requirements of typical BMS controllers that operate at sampling rates of 1–10 Hz, confirming the feasibility of deploying the trained model in real-time embedded applications.

C. Real-Time Prediction Simulation

A real-time prediction simulation was conducted across all 20 battery cells by streaming the test sequences in chronological order and recording the model prediction at each timestep. The cluster-state label at each prediction point was overlaid on the voltage waveform to visualize state transitions. The simulation confirms that Cluster 1 (mid-plateau) dominates the discharge period (approximately 70–80% of each cell's lifecycle), with transitions to Cluster 0 at end-of-discharge and Cluster 2 at end-of-charge occurring within 3–5 cycles of the nominal transition boundaries.

Across all 20 cells, the CNN-LSTM maintained stable prediction accuracy with no catastrophic degradation on any individual cell, demonstrating that the per-cell sequence generation strategy effectively prevents cross-cell interference and generalizes to unseen manufacturing variability.

VIII. DISCUSSION

The experimental results validate two central design decisions. First, the 1D convolutional front-end adds significant value by compressing the 30-timestep, 9-feature input into a 14-timestep, 32-feature representation before the LSTM processes it. This compression reduces the effective sequence length that the LSTM must model, alleviating the gradient vanishing problem that typically limits recurrent networks on long sequences. The convolutional kernels learn to detect transient discharge events such as voltage dips at cycle onset and thermal spikes during fast charging, features that would require many LSTM hidden units to detect directly.

Second, the K-Means cluster-state feature provides the model with an explicit encoding of the electrochemical regime, allowing the LSTM to condition its internal dynamics on the current phase of the discharge curve. Without this feature, the LSTM must implicitly infer the discharge regime from the voltage trajectory alone, which is particularly difficult at the plateau boundaries where voltage changes slowly and regime transitions are ambiguous from a purely local signal perspective.

The compact parameter count of the CNN-LSTM (54,417 parameters) represents a practical advantage for edge deployment in automotive BMS controllers, where memory constraints typically limit model size to below 512 KB. The corresponding 54 KB parameter footprint (in 32-bit float) easily satisfies this constraint. The inference latency of 0.12ms per sample further confirms the suitability of the model for real-time operation at standard BMS sampling rates.

IX. CONCLUSION

This paper presented a CNN-LSTM hybrid deep learning architecture for real-time Li-ion battery terminal voltage prediction. The proposed pipeline integrates a K-Means cluster-state augmentation stage that encodes the three electrochemical discharge plateau phases as an additional input feature, enhancing the model's ability to adapt its temporal dynamics to the current operating regime. Rigorous data leakage prevention through cell-level train/test splitting and per-cell sequence generation ensures that reported metrics reflect genuine generalization to unseen battery cells.

The CNN-LSTM model achieved an R^2 of 0.9521,msE of 0.0012, and MAE of 0.0230 on the held-out test cells, with per-cluster analysis confirming strong performance across all three electrochemical regimes. The model's compact size (54,417 parameters) and low inference latency (0.12ms/sample) make it suitable for real-time deployment in embedded BMS applications.

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REFERENCES

[1] H. Kim, J. Lee, and S. Park, “CNN-LSTM-Based State of Charge Estimation for Lithium-Ion Batteries Under Dynamic Driving Conditions,” IEEE Access, vol. 11, pp. 45231–45245, 2023.

[2] Y. Li, X. Zhang, and H. Wang, “Deep Learning-

Based Battery Voltage Prediction Using Hybrid CNN-LSTM Networks," Journal of Energy Storage, vol. 68, Art. no. 107892, 2023.
[3] T. Wang, Y. Zhao, and K. Liu, "Hybrid CNN-LSTM Architecture for Lithium-Ion Battery Health Monitoring in Electric Vehicles," Energy Reports, vol. 9, pp. 8123–8135, 2023.
[4] J. Zhang, H. Chen, and Y. Sun, "LSTM-Based Remaining Useful Life Prediction for Lithium-Ion Batteries," Applied Energy, vol. 332, Art. no. 120512, 2023.
[5] M. Chen, R. Zhou, and X. Li, "Convolutional Neural Network Approach for Battery Feature Extraction and Monitoring," IEEE Transactions on Industrial Electronics, vol. 70, no. 9, pp. 8841–8850, 2023.
[6] Y. Liu, P. Wang, and D. Xu, "Battery Voltage Forecasting Using CNN-Assisted Recurrent Neural Networks," Journal of Power Sources, vol. 603, Art. no. 233942, 2024.
[7] Z. Huang, J. Wu, and Q. Lin, "Deep Sequential Learning for Lithium-Ion Battery State of Health Estimation," Energy AI, vol. 14, Art. no. 100281, 2024.
[8] X. Zhao, Y. Cheng, and S. Li, "Data-Driven CNN-LSTM Framework for Battery Charging Behavior Analysis in Electric Vehicles," IEEE Access, vol. 12, pp. 45677–45691, 2024.
[9] K. Sun, H. Yu, and J. Ma, "Hybrid CNN-LSTM Deep Learning Architecture for Real-Time Battery Monitoring," Electronics, vol. 13, no. 4, Art. no. 745, 2024.
[10] P. Xu, Z. Deng, and M. Qian, "Temporal Deep Learning Model for Lithium-Ion Battery Voltage Prediction," Energy Reports, vol. 10, pp. 2104–2116, 2024.
[11] L. Yang, H. Zhao, and X. Chen, "Battery Fault Diagnosis Using CNN-LSTM Networks for Electric Vehicle Applications," IEEE Transactions on Transportation Electrification, vol. 10, no. 2, pp. 1785–1796, 2024.
[12] Y. Ma, S. Wang, and T. Huang, "Intelligent Battery Management Using Deep Sequential Learning Networks," Journal of Energy Storage, vol. 72, Art. no. 108415, 2024.
[13] C. Peng, J. Liu, and Y. Fang, "Multivariate CNN-LSTM Model for Electric Vehicle Battery Parameter Prediction," Applied Thermal Engineering, vol. 245, Art. no. 122873, 2024.
[14] R. Wu, X. Sun, and P. Li, "Attention-Assisted LSTM Network for Battery Performance Forecasting and Degradation Analysis," Energy, vol. 301, Art. no. 131912, 2024.
[15] A. Sharma, K. Verma, and R. Patel, "Hybrid CNN-LSTM Based Battery Management System for Real-Time Voltage Estimation," International Journal of Electrical Power and Energy Systems, vol. 161, Art. no. 110245, 2025.